Statistical-Dynamical Predictions of Seasonal North Atlantic Hurricane Activity

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ABSTRACT

Skillfully predicting North Atlantic hurricane activity months in advance is of potential societal significance and a useful test of our understanding of the factors controlling hurricane activity. We describe a statistical-dynamical hurricane forecasting system, based on a statistical hurricane model, with explicit uncertainty estimates, built from a suite of high-resolution global atmospheric dynamical model integrations spanning a broad range of climate states. The statistical model uses two climate predictors: the sea surface temperature (SST) in the tropical North Atlantic and SST averaged over the global tropics. The choice of predictors is motivated by physical considerations, results of high-resolution hurricane modeling and of statistical modeling of the observed record. The statistical hurricane model is applied to a suite of initialized dynamical global climate model forecasts of SST to predict North Atlantic hurricane frequency, which peaks in the August-October season, from different starting dates. Retrospective forecasts of the 1982-2009 period indicate that skillful predictions can be made from as early as November of the previous year – that is, skillful forecasts for the coming North Atlantic hurricane season could be made as the current one is closing. Based on forecasts initialized between November 2009 and March 2010, the model system predicts that the upcoming 2010 North Atlantic hurricane season will likely be more active than the 1982-2009 climatology, with the forecasts initialized in March 2010 predicting an expected hurricane count of eight and a 50% probability of counts between six (the 1966-2009 median) and nine.

1- Introduction:

Substantial attention has been placed in developing forecast systems for the seasonal activity of North Atlantic hurricanes and tropical storms, with various methods developed over the years (see review in Camargo *et al.* (2007)). Seasonal basin-wide activity forecast systems have been developed showing skill in retrospective forecasts over many years starting from April through July for the hurricane season that peaks in August-October (*e.g.,* Gray 1984, Elsner and Jagger 2006, Vitart 2006, Vitart *et al.* 2007, Klotzbach and Gray 2009, LaRow *et al.* 2010, Wang *et al.* 2009, Zhao *et al.* 2010). In general, one can view the hurricane prediction problem as a two-step process: i) predicting the state of the future climate system on large scales (the climate prediction), and ii) predicting the response of basin-wide hurricane frequency to that future climate state (the hurricane prediction). Sometimes the two steps occur within a single process, such as when dynamical coupled climate models are used to predict the state of future climate, and the response of the hurricane-like vortices in the models is used to estimate future hurricane activity (*e.g.,* Vitart 2006, Vitart *et al.* 2007), or when a statistical relationship between conditions prior to the hurricane season and the future season's hurricane activity is used (*e.g.,* Gray 1984, Elsner and Jagger 2006, Klotzbach and Gray 2009). Since both the evolution of the climate system and the response of hurricane activity to climate are chaotic processes, these forecasts are necessarily probabilistic.

The methods developed to date have been shown to have skill at predicting basin-wide tropical cyclone statistics in the North Atlantic from the summer (Vitart 2006, Klotzbach and Gray 2009, LaRow *et al.* 2010, Zhao *et al.* 2010), and as early as spring (Vitart *et al.* 2007, Wang *et al.* 2009). Here we develop a statistical-dynamical forecast

system to extend the lead-time of the forecasts to the winter prior to the hurricane season, with explicit uncertainty estimates.

Our approach is to build on recent results with the NOAA/GFDL High-Resolution Atmospheric Model (HiRAM-C180; Zhao *et al.* 2009, 2010), a model that is able to recover much of the observed year-to-year variations in North Atlantic hurricane frequency when forced with observed SST. We take advantage of a variety of experiments that have been performed to date with this dynamical model across a broad range of climates to develop a statistical emulation of the sensitivity of hurricane frequency to SST in this dynamical model, the statistical formulation of the emulator is based on the results of Villarini *et al.* (2010a) and motivated by physical considerations. The emulator is applied to dynamical predictions of SST from two initialized coupled modeling prediction systems in order to make predictions of Atlantic hurricane frequency. We use retrospective forecasts over the period 1982-2009 to assess the skill our method, and we make forecasts for the upcoming (2010) hurricane season.

2. Methods:

a.   *High-Resolution Atmospheric Model*

Our hybrid forecasting technique is built on the results from a dynamical hurricane climate model recently developed at NOAA's Geophysical Fluid Dynamics Laboratory (GFDL), the High-Resolution Atmospheric Model (HiRAM), specifically the HiRAM-C180 (cubed sphere dynamical core (*Putman and Lin 2007*) with 180×180 grid points on each face of the cube, resulting in grid sizes ranging from 43.5 km to 61.6 km). When forced with observed sea surface temperatures (SSTs) of *Rayner et al.* (*2003*), the

HiRAM-C180 model simulates hurricane statistics that compare well with the observations for the period of 1981-2008 (*Zhao et al. 2009, 2010*). The model recovers the overall geographical distribution of storm genesis locations, as well as the seasonal cycle and the interannual variability of hurricane frequency for the North Atlantic and the East and West Pacific.

The quality of our dynamical model forced with the observed SSTs has encouraged us to use this model as a tool to explore issues related to seasonal hurricane predictions. As a first step, Zhao *et al.* (2010) used HiRAM-C180 to pursue retrospective predictions of seasonal hurricane frequency in the North Atlantic and East Pacific by simply persisting SST anomalies from June throughout the hurricane season (these are effectively persistence forecasts initialized in July). Using an ensemble of five realizations for each year between 1982 and 2008, the correlation of the model mean with observations of basin-wide hurricane frequency is 0.69 in the North Atlantic. Furthermore, Zhao *et al.* (2010) found that a significant part of the degradation in skill (compared to a model forced with observed SSTs (correlation=0.78) during the hurricane season) can be explained by the change from June through the hurricane season in one parameter, the difference between the SST in the main development region and the tropical mean SST. This indicates that the quality of seasonal forecasts based on a coupled atmosphere-ocean model will depend in large part on the model's ability to predict the evolution of the difference between main development region SST and tropical mean SST.

In Zhao *et al.* (2009), the same dynamical model was also used to simulate the hurricane response to four different SST anomalies generated by coupled models in the

Third Coupled Model Intercomparisson Project (Meehl *et al.* 2007, CMIP3) archive, for the late 21st century based on the A1B scenario. The SST anomalies were obtained from single realizations of three models (GFDL's CM2.1, UKMO's HADCM3, and MPI's ECHAM5), and from the ensemble mean for the simulations for 18 models.

Since the Zhao *et al.* (2009) study, we have further pursued five additional SST warming experiments using SSTs from different coupled models (GFDL's CM2.0, UKMO's HADGEM1, CCCMA's CGCM, MRI CGCM2.3.2, and CCSR MIROC-HI model). As described in Zhao *et al.* (2009), we generated a control simulation by prescribing the climatological SST (seasonally varying with no interannual variability) using time-averaged (1982-2005) HadISST data (Rayner *et al.* 2003). We then add the SST warming anomalies (also seasonally varying with no interannual variability) projected by the coupled model to the climatological SST to pursue the global warming experiments. Ten-year integrations were carried out for both the control and the perturbation experiments.

b.   *Statistical Hurricane Model*

Ideally, we would like to use as our hurricane forecast tool a global dynamical modeling system like that of Zhao *et al.* (2009, 2010), which exhibits both substantial skill in retrospective hurricane frequency integrations with prescribed SSTs and represents the response of hurricanes across a broad range of possible climate states. However, the computational expense of running this high-resolution model over the hundreds of retrospective forecast experiments needed to assess the retrospective skill of the model is prohibitive. Our approach in this work is to take advantage of the hundreds of years of experiments with the HiRAM-C180 model across a broad range of climates to

develop a statistical emulation of this dynamical model, which will have the advantage of being computationally inexpensive, allowing us to perform the hundreds of retrospective forecasts needed. In addition, we will train this statistical emulator on both the historical HiRAM-C180 experiments as well as a suite of experiments exploring substantially altered climate states, in order to build a statistical system that is more likely to be robust across different possible climates, and not optimized to retrospectively predicting past climate. An additional advantage is that once it is developed, the statistical model can be applied to a wide range of SST forecast products, *e.g.*, by applying it to seasonal SST forecasts from various operational centers.

To build our statistical emulation of HiRAM-C180 we must select a set of potential climate-state covariates to serve as predictors. We focus on covariates based on SST since the results of Zhao *et al.* (2009) strongly suggest that a large fraction of the climate information for hurricane activity is contained in the monthly evolution of global patterns of SST. For this work, we wish to build as parsimonious a statistical model of basin-wide hurricane frequency as possible, but one that is still able to describe the variability exhibited by the data. For this reason, we limit our predictors to two: Atlantic Main Development Region SST (SST_{MDR}) and Tropical-Mean SST (SST_{TROP}). We choose as one possible predictor SST_{MDR} (SST averaged over 80°W-20°W, 10°N-25°N, averaged over August-October, the peak months of the hurricane season), since we expect hurricane activity in the Atlantic to depend partly on the evolution of SST local to hurricane development (*e.g.,* Emanuel 2005, Mann and Emanuel 2006, Vecchi and Soden 2007, Swanson 2008, Knutson *et al.* 2008, Zhao *et al.* 2009, Villarini *et al.* 2010a). In addition, we choose as another possible covariate SST_{TROP} (SST averaged 30°S-30°N and

during the period August-October) because: *(i)* there is a substantial body of evidence that tropical-mean SST changes can influence large-scale climatic conditions in the North Atlantic that affect hurricane activity, such as wind shear (Latif *et al.* 2007), upper tropospheric temperature (Sobel *et al.* 2002) that in turn influences hurricane potential intensity (Vecchi and Soden 2007) and other measures of thermodynamic instability (*e.g.,* Shen *et al.* 2000, Tang and Neelin 2004), (*ii*) tropical-mean SST appears to be a useful covariate in the description of the historical changes in other measures of basin-wide tropical cyclone activity in the North Atlantic (*e.g.,* Swanson 2008, Vecchi *et al.* 2008, Villarini *et al.* 2010a), and *(iii)* the differences between tropical Atlantic and tropical-mean SST are a good description of the climate response of hurricane frequency in high resolution atmospheric models (*e.g.,* Knutson *et al.* 2008, Zhao *et al.* 2009, 2010, Villarini *et al.* 2010b). We expect *a priori* that SST_{MDR} will emerge as a positively correlated predictor of hurricane frequency, while SST_{TROP} should emerge as a negatively correlated predictor.

To emulate the response of hurricane frequency to changes in SST in HiRAM-C180, we use a Poisson regression model in which the rate of occurrence λ is a function of both SST_{MDR} and SST_{TROP}. The statistical model is built from 212 years of model integration from HiRAM-C180 (Figure 1), which include ten ten-year climate change experiments (each of the ten experiments explores the hurricane response to a different projection of 21st Century SST from the IPCC-AR4/CMIP3 archive) and four historical ensembles in which the model was forced with the observed SSTs (*Rayner et al. 2004*) over the period 1981-2008 (Zhao *et al.* 2009, 2010). We then build a Poisson regression model (using the gamlss R-Package; Stasinopoulos *et al.* 2007) for the HiRAM-C180 hurricane counts to

the corresponding SST_{MDR} and SST_{TROP}. Our training was performed on anomalies relative to the 1982-2005 average. We also performed sensitivity experiments by training the statistical model separately on the four member historical experiment set of HiRAM-C180 and on the suite of climate change experiments. For all of the training experiments, both tropical Atlantic and mean tropical SSTs are retained as significant predictors; the coefficients of these two covariates have similar magnitudes but opposite signs (SST_{MDR} acting as a positive predictor and SST_{TROP} as a negative one, conforming to our prior expectation). More specifically, in each of the training experiments the magnitude of the influence of SST_{TROP} is always larger than that of SST_{MDR}, indicating a tendency of uniform tropical-mean warming (SST_{MDR}=SST_{TROP}) to reduce Atlantic hurricane frequency, and consistent with the sensitivity of historical North Atlantic tropical-storm frequency (Villarini *et al.* 2010a). We retain as our "best" emulator the model fitted to the entire record, since it spans the broadest range of possible climate conditions, giving us more confidence as to its applicability to novel situations. When trained on the entire suite of HiRAM-C180 experiments (exploring both historical and climate change conditions), the rate of occurrence λ of the Poisson regression model can be described as a linear function of both SST_{MDR} and SST_{TROP} (via a logarithmic link function) as follows:

$$\lambda = e^{1.707 + 1.388 \cdot SST_{MDR} - 1.521 \cdot SST_{TROP}} \qquad (1)$$

Where SST_{MDR} and SST_{TROP} are anomalies in the regional SST indices relative to the 1982-2005 average.

As can be seen in Fig 1, the fitted statistical model is able to reproduce well the variability exhibited by the basin-wide hurricane counts under different conditions (both

in the HiRAM-C180 response to historical SST changes and to large climate change

projections), providing supporting evidence of its robustness. Evaluation of the model fit

was performed by visual examination of the residual plots (e.g., qq-plots and worm

plots), as well as computing residuals' statistics, such as mean, variance, skewness,

kurtosis, and Filliben correlation coefficient (consult Villarini *et al.* (2010a) for a more

extensive discussion about model fitting and evaluation); these assessments of the

model's residuals supported the model's selection.

To test the relevance of this statistical emulator of a global dynamical model to the

observed record we apply the emulator to the observed August-October SST indices (Fig.

2). The statistical emulator recovers much of the observed variability in hurricane

activity, with a correlation coefficient of 0.76 and a root-mean square error (RMSE) of

1.99 hurricanes over the period 1982-2009. These values compare very well to the 1982-

2008 correlation of 0.79 and RMSE of 1.86 hurricanes from the full HiRAM-C180

AGCM when forced with observed monthly varying SST field (Zhao *et al.* 2009, 2010).

Therefore, despite its parsimony (only two predictors), our simple hurricane statistical

model performs very well, and there is little statistical justification for adding predictors

to our emulator since the correlation to the observed record is so similar to that of the full

high-resolution dynamical model we are seeking to emulate.

    c.   *Forecasts of Sea Surface Temperature*

We explore two initialized forecast systems built on coupled ocean-atmosphere

models: the NOAA Geophysical Fluid Dynamics Laboratory (NOAA/GFDL) Climate

Model v.2.1 (CM2.1) experimental seasonal-to-interannual prediction system, and the

NOAA National Center for Environmental Prediction (NOAA/NCEP) Climate Forecast System (CFS).

The NOAA/GFDL experimental S-I prediction system is built on the NOAA/GFDL CM2.1 coupled climate modeling system (Delworth *et al.* 2006), which was also used to provide data for the recent Fourth Assessment Report of the Intergovernmetal Panel on Climate Change (IPCC-AR4). The GFDL-CM2.1 retrospective forecasts consist of a set of retrospective predictions initialized over the period November 1981 through March 2010, each with a 10-member ensemble initiated from the first day of every month (November to August) with an integration of 12 months. Thus, for each of 28 August-October seasons (1982-2009) we have 100 retrospective integrations (10 ensemble members initialized in each of the 10 months). In addition, we have 10-member forecasts for the upcoming 2010 hurricane season initialized 1-November-2009 through 1-March-2010.

The state of the ocean and atmosphere for each of the GFDL-CM2.1 forecast experiments is set using a state-of-the-art coupled (ocean-atmosphere) ensemble Kalman Filter (EnKF) assimilation system, which incorporates the observed oceanic and atmospheric state available prior to the initiation of the forecast run (Zhang *et al.* 2007). The initial conditions for the ten ensemble members for each forecast experiment are selected from the ensemble members of the EnKF initialization scheme. The ten ensemble members of each forecast experiment were used to calculate the ensemble mean climatology, with each start month having its own separate climatology to correct for systematic model drift. For each of the forecast initialization times (1-November through 1-August) we computed 1-August(0)-31-October(0) SST anomaly (relative to

each the forecast system's 1982-2005 climatology) indices for the Atlantic MDR and tropics.

We also use SST forecasts from the current NCEP operational Climate Forecast systems (CFS) model (Saha *et al.* 2006). The CFS is a fully coupled ocean-land-atmosphere dynamical seasonal prediction system, and forecasts are initialized from the observed estimates of the ocean, atmosphere, and land conditions. Various elements of the CFS consist of the NCEP Global Forecast Systems version 2003 and the Geophysical Fluid Dynamics Laboratory Modular Ocean Model version 3. Initial conditions for the CFS are taken from the NCEP/DOE Reanalysis-2 (R2) for the atmosphere and land, and from a NCEP Global Ocean Data Assimilation System (GODAS) for the ocean.

For each month (January through July) in the NCEP-CFS forecast period (1982-2009), 15 forecast members were produced by the CFS for the nine following (target) months. The 15 forecast members are in a group of three sets with 5 members each. The three sets of forecast runs are initiated from 00Z around the 1st, 11th, and 21st calendar day of the month. The five members in each set of the forecast runs are from five observed atmospheric and land initial conditions that are one day apart, but share the same oceanic initial condition.

For comparing the various retrospective forecasts we use the convention that a Month-M forecast should include data no more recent than the first week of month M in its initialization, so that we are assessing the ability to issue a hurricane forecast early in month M. Thus, the GFDL-CM2.1 Month-N forecasts are the ten-member ensemble initialized on the 1st day of that month, for NCEP-CFS Month-M forecasts are the 15 member ensemble made up of the ten members initialized on the 11th and 21st of month

M-1 and the five members initialized on the 1st of month *M*, and for SST persistence the

Month-*M* forecasts are those in which SST anomalies from month *M-1* are persisted.

d.   *Seasonal Hurricane Forecasts and Uncertainty Estimates*

In order to perform our hybrid statistical-dynamical forecasts of hurricane frequency,

we take the dynamical predictions of SST_{MDR} and SST_{TROP} and use them as input for our

statistical emulation of the HiRAM-C180 high-resolution dynamical atmospheric model.

In our seasonal forecasts of hurricane frequency we wish to explicitly compute

uncertainty estimates arising from two sources that we can currently quantify: *(i)* given

an initial state of the climate system the forecasts of the SST indices are uncertain, with

variations arising due to the chaotic nature of the global climate system, and *(ii)* given a

particular realization of SST the forecasts of hurricane frequency are uncertain, due to

variations in hurricane frequency that are not constrained by our SST indices. We can

estimate the uncertainty arising from *(i)* by exploring the ensemble suite of the initialized

forecasts, and we can estimate the uncertainty arising from *(ii)* through the parametric

probability estimates in the Poisson model of hurricane frequency given a rate parameter

(λ) (Rice 1995*, p41*):

$$p(Count = k \mid \lambda) = \frac{\lambda^k e^{-\lambda}}{k!} \quad [k=0,1,2....] \tag{2}$$

To compute our predictions of hurricane activity we first, for each initialization, take

the predicted August-October SST_{MDR} and SST_{TROP} from each of the ensemble members

(anomalies computed from the forecast system 1982-2005 climatology). We then apply

these indices to the fit to obtain the predicted rate parameter λ from our Poisson fit

emulator of the HiRAM-C180 model (Eq. 1), and from Eq. 2 we can compute the

probability density function (PDF) of predicted hurricane counts for each of the ensemble members. We then convolve the PDFs from the suite of forecast ensemble members in order to arrive at an ensemble PDF for each month of initialized forecasts:

$$p(Count = k \mid Initialization) = \frac{1}{N} \sum_{i=1}^{N} p(Count = k \mid \lambda_i) \qquad (3)$$

, where λ_i is the rate parameter computed from the ith ensemble member for a given initialization month's forecast, and N is the number of ensemble members available. With this PDF, we can compute an expected value (mean), as well as various confidence intervals and exceedance probabilities in the counts for each year and for each forecast month.

We use two ensemble-averaging techniques to generate our predictions of annual hurricane frequency. The first technique is a simple ensemble average, in which we take the ensemble members that are initialized using data from the month just prior to a given month as the total ensemble set. The second technique is the lagged super-ensemble, which is motivated by a desire to increase the ensemble size from ten/fifteen, and results from the constraints on the size of the ensemble that have been run. In this lagged super-ensemble we build a thirty-member ensemble set consisting of the three ten-member ensembles initialized that particular month and the two preceding months for GFDL-CM2.1, and of the two fifteen-member ensembles initialized by the particular month and that preceding it for NCEP-GFS. The assumption in generating the lagged super-ensemble is that the error growth over the period between the initialization of the oldest ensemble set and the newest is smaller than the enhanced fidelity of additional ensemble members. This assumption is justified *a posteriori* by the examination of the behavior of our retrospective forecasts presented below. We can compute a two-model ensemble by

using as the set of SST forecasts the total ensemble from NCEP-CFS and GFDL-CM2.1, which for monthly forecasts is 25 and for lagged ensembles is 60.

3. Retrospective Forecast Results:

In this section we explore the retrospective skill of our basin-wide hurricane frequency forecast system. To assess the skill of the predictions of hurricane frequency based on the SST forecasts from GFDL-CM2.1 and NCEP-CFS, we compare them against the persistence of anomalies in SST_{MDR} and SST_{TROP} from the Rayner *et al.* (2003) dataset. As shown in Zhao *et al.* (2010), we expect a sharp drop-off in the skill of persistence forecasts across late Boreal Spring. Our hope is that, by initializing the coupled ocean-atmosphere system from observations and representing the dynamical and thermodynamical processes that control the evolution of the climate system, the dynamical forecast systems could extend the forecast window into Boreal Winter.

In these retrospective forecasts, we perform forecasts of hurricane activity in past years attempting to keep out information that would not have been available at the time of the forecast. It must be acknowledged that the construction of our hurricane prediction scheme is not entirely independent of the historical hurricane record (albeit in an indirect manner), as we decided to build a statistical emulation of the HiRAM-C180 atmospheric model because it is able to recover much of the historical hurricane frequency when forced with historical SST (Zhao *et al.* 2009, 2010). However, the HiRAM model was not optimized to recover the year-to-year variations of hurricane frequency (Zhao *et al.* 2009), and therefore the observed hurricane variations did not go into its construction; moreover, in building the statistical emulator we did not use the observed hurricane

record (which we seek to retrospectively forecast), but used only the HiRAM-C180 response to observed SST as well as to a suite of global climate change simulations. In doing so, we have attempted to minimize the direct influence of the observed hurricane record in our retrospective forecasts.

Figure 3 illustrates the retrospective skill in hurricane counts of the forecast system in two initialization months (January and March) and using the two ensemble averaging techniques (simple ensemble and lagged super-ensemble); since the hurricane season peaks in August-October these can be considered seven- or five-month lead forecasts. Since January initialized forecasts of August-October are not available from NCEP-CFS so the upper panels show the confidence intervals from the GFDL-CM2.1 based forecast, while the lower panels show the confidence intervals from the two-model (NCEP-CFS + GFDL-CM2.1) forecasts. In each of the panels in Fig. 3 the various ensemble averages of the forecast systems, though not perfect, exhibit some visual similarity to the observed hurricane record. For the retrospective forecasts shown in Fig. 3, the uncertainty estimates seem conservative, with nominally fewer than 25% and 10% of the cases outside the 75% and 90% confidence intervals, yet this difference is not statistically significant, and over the entire forecast suite there is no systematic bias in the uncertainty estimate. Measures of correlation and RMSE bear out the visual similarity of the observed and forecast time series, with correlations between 0.5-0.6 and RMSE of 2.4-2.6 hurricanes per year.

Among the years that were problematic for the system to retrospectively predict was the incredibly active season of 2005. None of the January or March retrospective forecasts were able to foretell in their mean estimate that 2005 should have been the most

active year over 1982-2005, much less its extreme value that lay outside the 90%

confidence interval for all forecasts (Fig. 3). However, with "perfect" SST values our

statistical emulator is able to recover that 2005 should have been the most active year

over 1982-2009 (Fig. 2), suggesting that predicting the evolution of our SST indices to

the values leading to an extreme hurricane season proved difficult for the dynamical SST

forecast systems. Furthermore, the observed counts for 2005 were outside the 90%

confidence interval of the statistical emulator even with perfect SST (Fig. 1.b), yet the

dynamical HiRAM-C180 model (Zhao *et al.* 2009) was able to recover this extreme

values using monthly fields of SST. This suggests that either non-linear dynamics

captured by the HiRAM-C180 framework but absent in our simplified statistical model or

the response to details in SST beyond our two indices were important to the extreme

2005 season. Further analyses should explore the key mechanisms that led to the extreme

2005 season.

We can use the correlation coefficients and RMSE from Zhao *et al.* (2009) and from

applying the statistically hurricane emulator to observed SST (r=0.78 and 0.76, and

RMSE = 1.91 and 1.99 hurricane/year, respectively) as estimates of the explainable

variance in hurricane counts from perfect knowledge of SSTs. In this context, our

retrospective forecasts initialized in January and March explain around half of this

explainable variance, with forecasts initialized in December and November exhibiting

slightly lower skill (Fig. 4).

The retrospective hurricane forecast skill as a function of initialization month is

compared to a variety of other estimates of predictability in Fig. 4. As one approaches

the hurricane season (forecasts initialized in June and later), the hurricane forecasts using

GFDL-CM2.1 forecasts of SST do not outperform persistence of SST anomalies (either with our statistical emulator or in the results of Zhao *et al.* (2010)). In contrast, the short-lead (July and August) hurricane forecasts using the NCEP-CFS system reach our estimates of potential predictability, with May and June forecasts approaching that measure. For longer lead times (April and earlier), the dynamical predictions of SST from both dynamical systems lead to substantial increases in hurricane forecast skill over those with persisted SST anomalies. All of the schemes, including the persisted SST anomaly schemes, outperform the trailing five-year average (gray dash dotted line in Fig. 4; a skill metric suggested by the World Meteorological Organization (WMO, 2008)) and the persistence of the previous season's hurricane frequency (correlation of 0.14 and RMSE of 3.83 hurricanes per year).

In Fig. 4 one can see that the retrospective skill (as measured by correlation and RMSE) of the ten- and fifteen-member simple ensemble forecasts (left panels) exhibit substantial variability from month to month; for example, the correlation for GFDL-CM2.1 reaches 0.66 in January but drops to 0.45 in February initializations before rising again to 0.49 for March initialization. On the other hand, the lagged super-ensemble predictions (right panels) exhibit not just stable skill in time, as one would expect from its inherent time smoothing, but also a consistently greater skill than the individual simple ensembles (except for January in GFDL-CM2.1 and the forecasts from boreal summer in NCEP-CFS). This difference in the behavior of the two types of ensemble strategies suggests that the forecast systems (particularly GFDL-CM2.1) could benefit from a larger ensemble set (e.g., 30 members instead of 10), and that – as was assumed above – over the time between the newest and oldest of the members of the super-ensemble, the impact

of error growth is smaller than the beneficial effect from additional ensemble members. Because of this, we view the lagged super-ensemble system as likely superior to the simple ensemble particularly at longer leads, though perhaps a larger ensemble set would be preferable to either.

The two-model ensemble forecast performs better than either model for forecasts initialized in late Boreal winter or early Boreal spring (Figs. 3, 4). As we approach the verification period, the skill exhibited by NCEP-CFS is sufficiently higher than that of GFDL-CM2.1 that the two-model ensemble performs worse than NCEP-CFS alone. These results would suggest that forecasts at long leads (April and earlier) should focus on the lagged ensemble, and when possible the two-model average, while for shorter leads forecasts using NCEP-CFS appear to be superior. For the November-January initializations we are limited to using the GFDL-CM2.1 forecasts of SST, since NCEP-CFS is not available.

4. Discussion:

We have built a statistical-dynamical North Atlantic hurricane frequency prediction scheme that exhibits skill since boreal winter prior to the hurricane season. The system was built using a statistical emulator of a high-resolution dynamical atmospheric model and initialized forecasts of SST. The forecast system predicts the probability density function of North Atlantic basin-wide hurricane frequency, thus uncertainty estimates are explicitly computed in the forecasts.

We have explored the predictability using a set of retrospective forecasts from a pair experimental forecasting system. The low computation cost of the statistical emulator

allows us to perform the hundreds of retrospective forecasts needed to establish its skill. In addition, this statistical framework can easily take advantage of data available from many dynamical forecast models at minimal additional cost. We find a slight indication that the skill of the long-lead (February and March initializations) seasonal forecasts is enhanced through the ensemble of GFDL-CM2.1 and NCEP-CFS forecasts of SST. This suggests that employing a "multi-model ensemble" approach (by combining a variety of climate forecasting systems to develop a "consensus" estimate) could be a useful extension of the current methodology. Multiple forecast centers around the world routinely make multi-season initialized forecasts of the state of the global climate system, from which one could easily extract the relevant predictors (tropical Atlantic and tropical-mean SSTs) to use in our hurricane prediction scheme. The simplicity and negligible computational cost of the statistical hurricane frequency emulator employed in our forecasts system, along with the explicit uncertainty estimates from convolving the uncertainty in SST with the uncertainty in hurricane frequency given SST, suggest that a multi-model ensemble modification to our technique is feasible.

Since El Niño variations impact seasonal North Atlantic hurricane frequency, it is reasonable to wonder whether our retrospective forecasts are only recovering skill from successful forecasts of El Niño. Although predicting the inactive hurricane frequency during some El Niño years (e.g., 1997) and the active frequency during some La Niña years (e.g., 1995 and 1998) contributes to the skill of the retrospective hurricane forecasts, the skill of the hurricane forecasting system exceeds the skill one would expect from El Niño alone: the correlation skill of the retrospective forecasts is higher than that between commonly used measures of El Niño and hurricane activity (0.5-0.6 vs. 0.4-0.5

in HiRAM-C180 and observations – Zhao *et al.* (2010)), and the El Niño forecasts in

GFDL-CM2.1 and NCEP-CFS are not perfect. Additional skill in seasonal hurricane

frequency may be coming from correctly predicting the coupled-atmosphere processes

that control seasonally phase-locked year-to-year variations in tropical Atlantic SST (e.g.,

Vimont and Kossin 2007, Doi *et al.* 2010).

Some of the retrospective skill comes from correctly diagnosing that the years before

1994 were more likely to be inactive, while later years had a greater tendency of being

active. The causes of that heightened activity remain a topic of discussion, with natural

climate variations, anthropogenic radiative forcing or changes in atmospheric dust

loading each likely contributing, though their relative influences remains a topic of active

inquiry (e.g., Mann and Emanuel 2006, Zhang and Delworth 2006, 2009, Evan *et al.*

2009). Both dynamical SST forecast systems (CM2.1 and CFS) capture the tendency for

increased frequency after 1995, as do the various persisted SST anomaly forecasts –

suggesting that the SST anomalies driving the multi-decadal increase in frequency are

principally seasonally invariant. Since the skill of the initialized hurricane predictions is

larger than that of the persisted SST anomaly forecasts and the WMO recommended

measure of the trailing five-year average (WMO 2008), both of which include aspects of

the multi-decadal shift, we see that the initialized forecasts include skill beyond correctly

diagnosing the multi-decadal increase in hurricane frequency.

The forecasting system has been developed for basin-wide hurricane frequency, yet

the results of statistical modeling tropical storms (Villarini *et al.* 2010a) and basin-wide

measures that combine intensity and frequency (Swanson 2008, Vecchi *et al.* 2008)

suggest that the procedure developed here could be adapted to these and possibly other

quantities in the North Atlantic. Further, Zhao *et al.* (2010) indicate that a statistical model using two SST indices can successfully describe East Pacific hurricane activity in the HiRAM-C180 model, suggesting that a methodology analogous to the current one may be applicable to East Pacific seasonal hurricane forecasts. We are currently investigating these and related topics.

For the upcoming hurricane season of 2010, this seasonal hurricane forecasting system predicts an above average number of hurricanes (see Table 1) – these predictions are quite similar to those from the various predictions with this system initialized since November 2009 (*e.g.,* see Fig. 3.a, 3.b). The prediction system forecasts that the upcoming season has a higher expected hurricane count than the average over the recent decades, along with a higher probability of an extreme (>10 hurricanes) number of hurricanes. This indicates that it should be more similar to the active years that have dominated the North Atlantic since 1995 than the very inactive season of 2009, and suggests that we should not conclude that (due to the relatively inactive 2006, 2007 and 2009 seasons) the multi-decadal period of heightened hurricane frequency has necessarily already abated.

Chang for their work on the GFDL-CM2.1 assimilation and forecast system, and to the

NCEP CFS team.

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Table 1:

	Mean Count (hurr)	Median (hurricanes)	p(count>6)	p(count>10)	p(count≤3)
Climatology 1982-2009	6.21	5	0.46	0.07	0.21
Climatology 1966-2009	6.14	6	0.39	0.07	0.16
Climatology 1995-2009	7.667	7.5	0.67	0.13	0.13
GFDL-CM2.1 Simple Ens.	9.88	9	0.80	0.39	0.03
GFDL-CM2.1 Lagged Ens.	8.27	8	0.64	0.24	0.09
NCEP-CFS Simple Ens.	7.64	7	0.61	0.19	0.04
NCEP-CFS Lagged Ens.	8.24	8	0.65	0.25	0.03
Two-model Simple Ens.	8.54	8	0.68	0.27	0.07
Two-model Lagged Ens.	8.23	8	0.75	0.25	0.08

Table Captions:

Table 1: Summary of the forecasts for the upcoming 2010 North Atlantic hurricane season initialized in March 2010. The first column indicates the source of the prediction, and the second row indicates the expected value from the 1982-2009 North Atlantic hurricane record. The second column indicates the average/expected count of North Atlantic hurricanes in the 2010 season, the third column indicates the median of the counts, the fourth and fifth columns indicate the probability of exceeding 6 hurricanes (the long-term average) and 10 hurricanes (an extremely active year), the sixth column indicates the probability of three or fewer hurricanes (an extremely inactive year). Notice that the forecasts are consistently suggesting that 2010 should be an active hurricane year relative to climatological values (upper two rows) and even relative to the recent period of heightened North Atlantic hurricane activity (third row).

Figure Captions:

Figure 1: Construction and evaluation of the statistical hurricane frequency model. Panel (a) shows the fit of the Poisson regression model of hurricane counts for the North Atlantic basin to the training set of HiRAM-C180 high resolution atmospheric model hurricane counts; blue dots show the counts from the HiRAM-C180 model, black line shows the median of the statistical model fit, green and gray shading show the 50% and 90%, respectively, confidence intervals on the fit. The simple statistical model, with only two covariates is able to capture the behavior of basin-wide hurricane counts across a broad range of climates in this dynamical atmospheric model.

Figure 2: Results of applying the statistical emulator of the sensitivity of HiRAM-C180 hurricane frequency to the observed sea surface temperature data of Rayner *et al.* (2003). Panel (a) shows a time-series plot of the observed hurricane counts (black line) and the expected counts from applying the statistical model to observed SST (blue line); the 90%, 75% and 50% confidence intervals the statistical fit are shown by the gray, yellow and green shading, respectively. Panel (b) shows a scatter plot of the observed hurricane counts versus the mean hurricane counts estimated by the statistical model from observed SST.

Figure 3: Retrospective 1982-2009 forecasts of North Atlantic hurricane frequency for (a, b) January and (c, d) March, for both the simple monthly ensemble (a, c), and the 30-member lagged ensemble (b, d). These plots illustrate the potential for long-lead

hurricane frequency forecasts from as early as January. In all the panels, the black line shows the observed North Atlantic hurricane count. The colored lines show the ensemble-averaged forecasts for the mean count using SST predictions from: the GFDL-CM2.1 system (red; CM2.1), the NCEP-CFS system (blue; CFS) and the two-system average (violet; MME). The blue dots show the forecasts of the mean count from the individual ensemble members. Color shading indicates estimates of uncertainty in the forecasts (the gray shading shows the 90% confidence range, the yellow shading shows the 75% confidence range and the pink shading shows the 50% confidence range). Confidence ranges are based on the GFDL-CM2.1 system in the upper panels, and on the two-system ensemble in the lower panels.

Figure 4: Performance of the dynamical-statistical S-I North Atlantic hurricane frequency forecast system as a function of forecast lead-time. The system skill is evaluated using (a, b) correlation and (c, d) RMSE, for both the simple monthly ensembles (a, c) and the lagged ensemble (b, d) schemes. The colored lines show the skill of the statistical-dynamical using GFDL-CM2.1 (red), NCEP-CFS (blue) and the two-model average (violet). The skill of the dynamical-statistical scheme is compared with two measures of "null skill": the WMO suggested standard (WMO 2008) of a lagged five-year average for evaluation of hurricane forecast skill (gray dash-dotted) and the statistical hurricane frequency model applied to the persistence of SST anomalies (solid gray and black lines, for persistence of monthly and three-month SST anomalies). Two measures of "potential skill" are shown: the performance of the statistical hurricane model using observed August-October SST (black dashed line) and the performance of

the HiRAM-C180 dynamical atmospheric model using observed monthly Rayner *et al.* (2003) SST fields from 1982-2008. For reference we show the Zhao *et al.* (2010) persisted June SST anomaly skill using the HiRAM-C180 dynamical atmospheric model (star symbol). The NCEP-CFS and two-model average schemes outperform the persistence forecasts for all months, and the GFDL-CM2.1 forecasts outperform persistence for all months prior to June.

Figure 5: As in the upper left panel in Figure 3, but for the June initialized retrospective 1982-2009 forecasts from GFDL-CM2.1. Notice that the forecasts deviate severely from observations over the period 2006-2008.
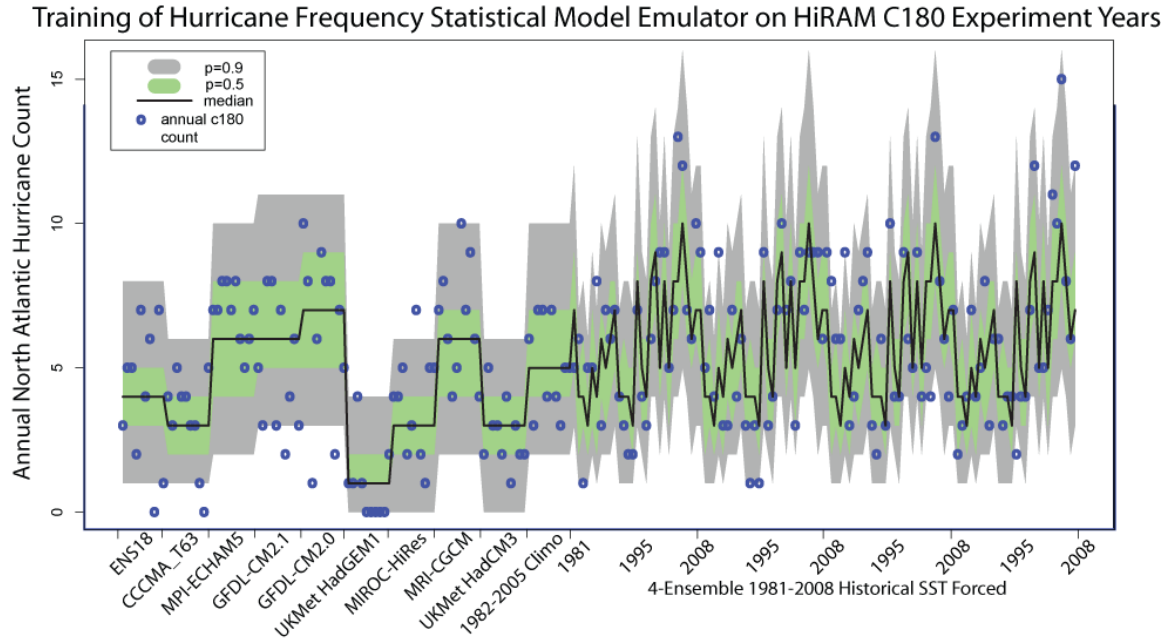
Figure 1: Construction and evaluation of the statistical hurricane frequency model.

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shows the median of the statistical model fit, green and gray shading show the 50% and

90%, respectively, confidence intervals on the fit. The simple statistical model, with only

two covariates is able to capture the behavior of basin-wide hurricane counts across a

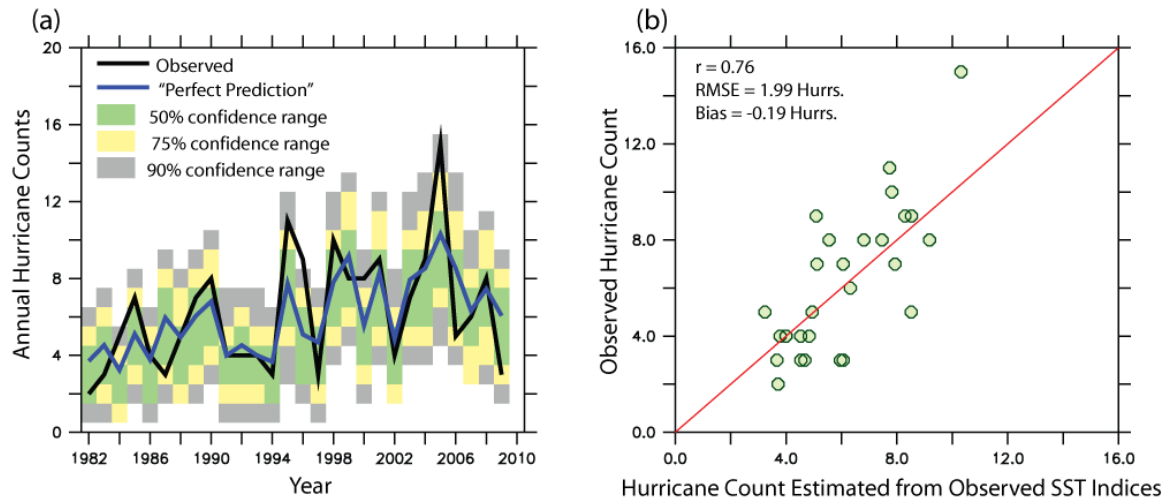broad range of climates in this dynamical atmospheric model.

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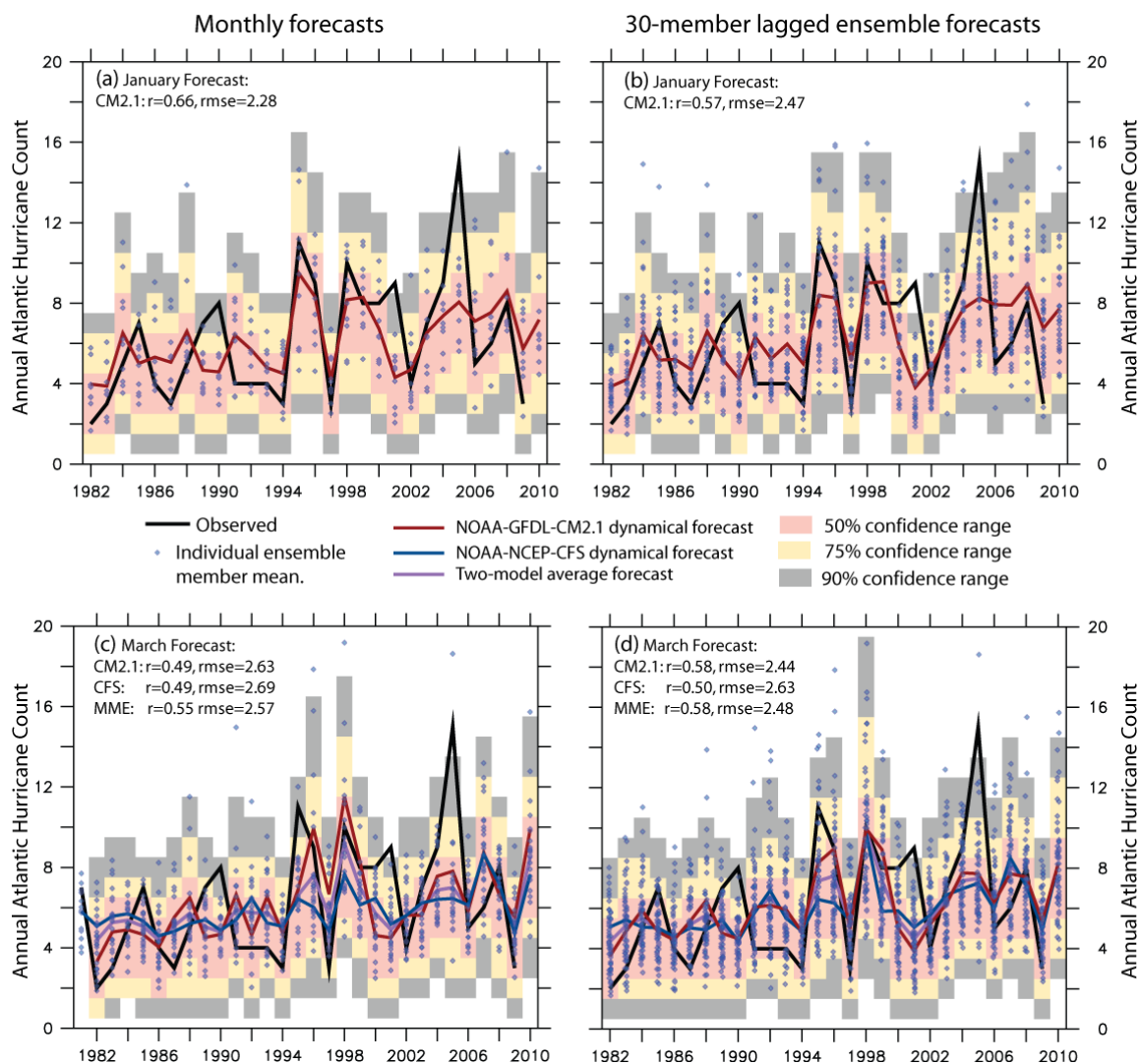
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forecasts (the gray shading shows the 90% confidence range, the yellow shading shows

the 75% confidence range and the pink shading shows the 50% confidence range).

Confidence ranges are based on the GFDL-CM2.1 system in the upper panels, and on the
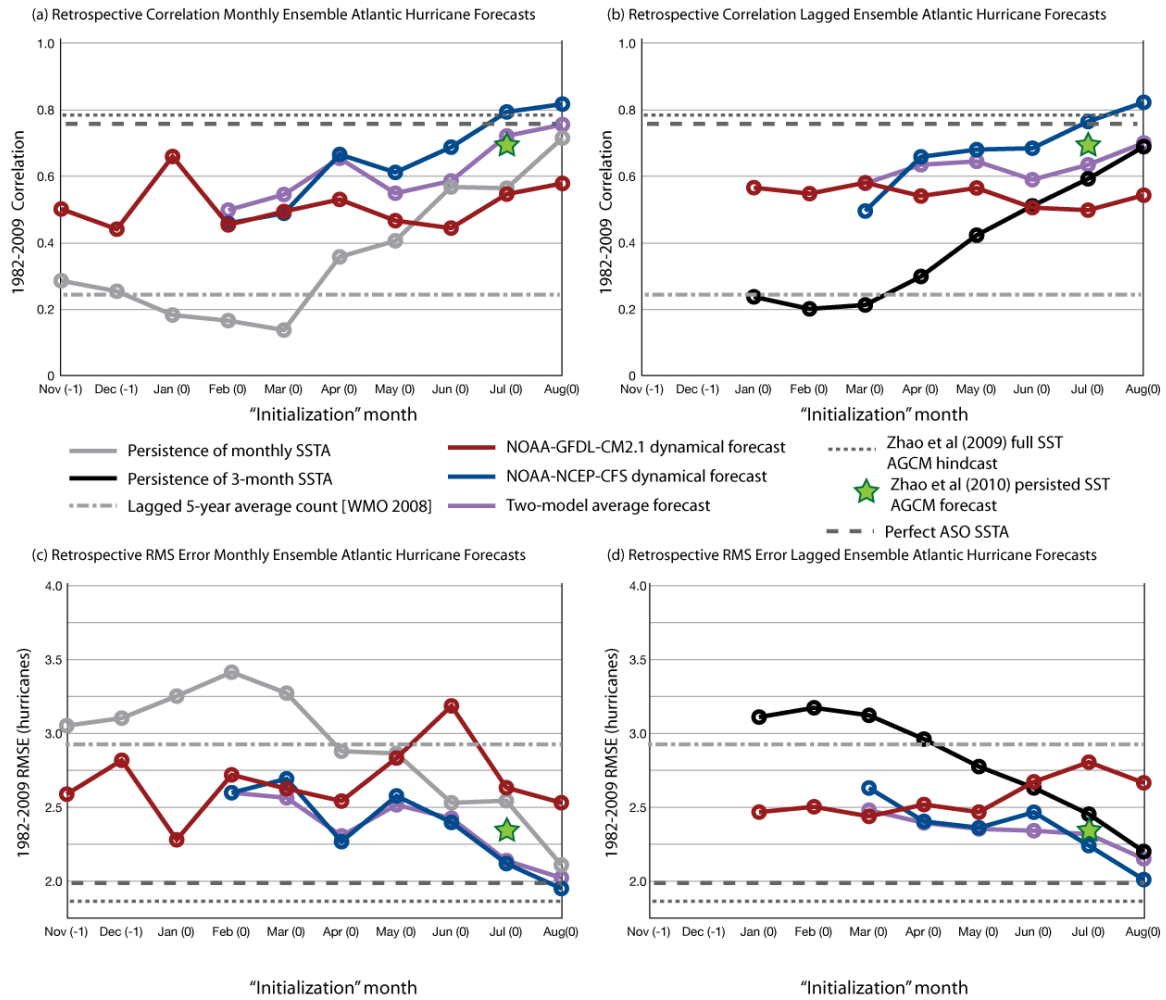
two-system ensemble in the lower panels.

Figure 4: Performance of the dynamical-statistical S-I North Atlantic hurricane frequency forecast system as a function of forecast lead-time. The system skill is evaluated using (a, b) correlation and (c, d) RMSE, for both the simple monthly ensembles (a, c) and the lagged ensemble (b, d) schemes. The colored lines show the skill of the statistical-dynamical using GFDL-CM2.1 (red), NCEP-CFS (blue) and the two-model average (violet). The skill of the dynamical-statistical scheme is compared with two measures of "null skill": the WMO suggested standard (WMO 2008) of a lagged five-year average for evaluation of hurricane forecast skill (gray dash-dotted) and the statistical hurricane frequency model applied to the persistence of SST anomalies (solid

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persistence for all months prior to June.